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Specialized human capital, unemployment risk, and the value premium

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Specialized human capital, unemployment risk, and the value premium

February 5, 2015

Abstract

To determine whether negative shocks to specialized human capital are priced in the cross section of stock returns, this study measures shocks to industry-specific human capital by employment growth in that industry. In industries in which employment contracts, exposure to the value factor is significantly higher than in industries in which employment expands. Cross-sectional predictive regressions and hedging portfolio returns document that stocks belonging to industries with low employment growth have higher expected returns than stocks belonging to industries with high employment growth. The return premium related to employment growth is pervasive across small, big, and micro stocks, as well as when micro stocks are excluded. The premium cannot be explained by the capital asset pricing model, but the hedging portfolio's payoffs are inversely related to that of the value-minus-growth risk factor.

Keywords: value premium, specialized human capital,
unemployment risk

JEL: G11, G12, J24, J60

1 Introduction

Human capital is an important component of household wealth. For example, income from salaries and wages accounted on average for 55% of U.S. personal income between 1980 and 2012.¹ Human capital also tends to be specialized and is often tied to a specific firm or industry, which can create investment challenges for households. Take, for example, a journalist working for a print newspaper. The Internet revolution of the mid-1990s dramatically changed the media sector, and the struggles of traditional media companies produced some bad prospects for employees. From a diversification standpoint, it is inadvisable for the journalist to invest in the company that employs him or her. The journalist's portfolio also would be poorly diversified if it contained mainly stocks from the media sector and related industries suffering from the same shock (e.g., print machine manufacturers). In general, a household should be concerned that a negative shock to its specialized human capital (non-financial wealth) is correlated with its financial wealth. Therefore, the household should prefer to avoid assets with a high correlation to its human capital and command a risk premium for holding such assets. The idea that specialized human capital is a possible source of a systematic risk factor – such as the value premium – originated with a conjecture by [Fama and French \(1996\)](#).²

This article considers explicitly whether negative shocks to industry-specific human capital are priced in the cross section of stock returns and related to the well-known value premium. I measure shocks to industry-specific human capital by using employment

¹Source: National Income and Product Accounts (NIPA), Table 2.1.

²In their terms ([Fama and French, 1996](#), p. 77): “Consider an investor with specialized human capital tied to a growth firm (or industry or technology). A negative shock to the firm's prospects probably does not reduce the value of the investor's human capital; it may just mean that employment in the firm will expand less rapidly. In contrast, a negative shock to a distressed firm more likely implies a negative shock to the value of specialized human capital since employment in the firm is more likely to contract. Thus, workers with specialized human capital in distressed firms have an incentive to avoid holding their firms' stocks. If variation in distress is correlated across firms, workers in distressed firms have an incentive to avoid the stocks of all distressed firms. The result can be a state-variable risk premium in the expected returns of distressed stocks.”

growth in the industry. In industries in which employment contracts, the exposure to the value factor is significantly higher than in industries in which employment expands. Using a cross-sectional predictive regression, I document that stocks belonging to industries with low employment growth have higher expected returns than firms belonging to industries with high employment growth. The predictive regression results imply a return difference between the lowest and highest employment growth deciles that amounts to 3.83%. The return premium related to industry employment growth is a robust feature of the data and pervasive across big, small, and micro stocks, as well as when micro stocks are excluded. The returns of a hedging portfolio that is long in stocks with high industry employment growth and short in stocks with low industry employment growth cannot be explained by the capital asset pricing model (CAPM), but the hedging portfolio's returns are inversely related to that of the value-minus-growth risk factor.

The value premium is widely studied in finance; it refers to the return differential between value and growth stocks. Value stocks are characterized by trading at a low price relative to fundamentals (e.g., book-value or earnings), whereas growth stocks are characterized by trading at a high price relative to fundamentals. The return spread between value and growth stocks cannot be captured by the static CAPM as numerous studies document (e.g., [Fama and French, 1992](#); [Lakonishok, Shleifer and Vishny, 1994](#)). The value anomaly also is not confined to the United States but persists internationally (e.g., [Rouwenhorst, 1999](#); [Fama and French, 2012](#); [Asness, Moskowitz and Pedersen, 2013](#)).

The value premium is generally regarded as a premium for relative distress. For example, [Fama and French \(1995\)](#) document that firms' book-to-market ratio relates negatively to profitability. Despite this link to the distress of *individual* firms, a satisfying connection to an *aggregate distress factor* has not been established. For instance, [Lakonishok et al. \(1994\)](#) show that the value premium barely differs in recessions compared with expansions.³ This

³Several other studies investigate the relation between the value premium and an aggregate macro factor of distress. [Vassalou and Xing \(2004\)](#) find that systematic default risk is only a partial source of

finding is particularly puzzling from a rational asset pricing perspective, which predicts that to be fundamentally riskier, value stocks should underperform growth stocks in bad states of the world, in which the marginal utility of wealth is high. This paper’s contribution is to show that the risk to specialized human capital, serving as explanation for the value premium, similarly exists not only in recessions but also throughout economic expansions.

The importance of human capital in relation to asset prices has long been recognized in the literature, at least back to [Mayers \(1972\)](#) and [Roll \(1977\)](#). The stock market return represents only an incomplete measure for the wealth portfolio of the CAPM by [Sharpe \(1964\)](#), [Lintner \(1965\)](#) and [Mossin \(1966\)](#) because it does not include human capital. To account for these deficiencies, several studies include labor income as a proxy for the return on human capital (e.g., [Fama and Schwert, 1977](#); [Campbell, 1996](#); [Jagannathan and Wang, 1996](#); [Santos and Veronesi, 2006](#)). Related to this line of literature, [Lettau and Ludvigson \(2001a,b\)](#) who show that deviations of consumption from its common trend with aggregate wealth (including both financial and non-financial wealth) possess predictive power for returns over time and in the cross section. The contribution of the current study is to increase our knowledge about how shocks to *specialized* human capital rather than *aggregate* human capital are priced in the cross section of stocks. The paper is closely related to that of [Eiling \(2013\)](#), who also investigates the relationship between industry-specific human capital and the cross section of stock returns, but differs in many important aspects. Whereas the latter focuses on industry-specific human capital in five distinct industries, I analyze employment shocks of a much broader cross section (up to 182 industries). Moreover, instead of looking at income growth, the current study focuses on industry-specific unemployment risk, and how it is priced in the cross section of stocks.

the value premium. [Vassalou’s \(2003\)](#) results suggest that news related the gross domestic product is contained in the value and size factors.

The results of this paper provide useful insights that can help tailor portfolio advice to different investors. According to [Cochrane \(2011\)](#), the differences in people’s exposures to risk, which could be hedged by systematic risk factors in the financial market, remain poorly understood. My results show that holding stocks of industries in which employment is contracting exposes the investor more to the value risk factor than does holding stocks of industries that are enjoying expanding employment. This finding suggests that an employee in an industry marked by decreasing employment should avoid a value investment strategy, since the returns will be correlated with the returns on his or her specialized human capital. An employee in a non-distressed industry instead may profit from a value investment strategy, effectively selling insurance to the employee of the distressed industry.

2 Measuring shocks to specialized human capital

I propose a novel measure for shocks to specialized (industry-specific) human capital, using employment growth at the industry level. In the following I explain the intuition behind this measure.

Human capital represents the present value of the cash flow stream derived from labor income. In many cases, human capital is specialized and linked to a certain industry. In my opening example, the journalist’s human capital is tied to the media industry. Similarly, an engineer working in the automobile industry possesses industry-specific human capital tied to that industry. If the industry is in distress, employment is likely to contract, and the specialized human capital of employees in that industry is at risk. The engineer could switch from the automobile industry to a different manufacturing industry, but only at the cost of specialized human capital, which most likely is reflected by a loss of income.

Industry-wide employment figures provide a good proxy of shocks to human capital tied to an industry. If only one firm in an industry is in distress, industry-specific human

capital is not at risk. Although an employee of this firm faces the risk of unemployment, she or he could find a job that requires similar tasks at a different company, with little loss in income. If the entire industry faces adverse times though, unemployment risk becomes greatly aggravated.

Using employment growth instead of wage growth as a proxy for shocks to human capital has several advantages. First, employment contraction, and therefore unemployment risk, in a particular industry captures the notion of displacement risk proposed by [Gârleanu, Kogan and Panagreas \(2012\)](#). Moreover, if an industry is in distress, wages measure the income decline of the workers employed, not of those who become unemployed. Second, wages are “sticky”, especially for downward adjustments. A negative shock to an industry might be reflected not in wages, but rather in the unemployment rate of the industry. Third, even for the workers who remain employed, rising unemployment in the specific industry represents a negative shock to their future labor income. The growing pool of unemployed workers with similar skills will reduce the bargaining power of the employed workers and, in the long run, result in lower real wage growth. Thus, employment expansion or contraction can be considered as a predictive indicator for future income growth in the specific industry sector.

This approach differs from previous studies (e.g., [Jagannathan and Wang, 1996](#)) that measure the return on aggregate human capital by the growth rate in per capita income. The latter approach measures *aggregate* human capital, whereas industry employment growth measures shocks to *industry-specific* human capital. Moreover, taking income growth as proxy for the returns on human capital does not account for additional investments in human capital during the period. A technology shock, for example, can create some jobs but at the same time destroy others. Looking solely at aggregate income, the two effects potentially cancel out, such that the income gains from new jobs compensate (or even over-compensate) for income losses due to destroyed jobs. However, the newly created

jobs likely are associated with a new technology and distinct skills, so they require a new investment in human capital. Employment growth across industries measures both (specialized) human capital destruction and creation.

What kind of shocks affect specialized human capital in different industries? In the journalist example, the shock to human capital is a technological shock, similar to that in Gârleanu, Panageas and Yu (2012) and Grammig and Jank (2012). But other shocks, such as rising competition from abroad, also potentially affect industries and therefore specialized human capital.

3 Data and descriptive statistics

Stock market data come from the U.S. Stock Databases from the Center for Research in Security Prices (CRSP). I apply commonly used filters, considering only ordinary common shares (share code 10 and 11) listed on the New York Stock Exchange (NYSE), the American Stock Exchange, the Nasdaq Stock Market, and the Arca Stock Market. Moreover, I require the stock to have a valid 3-digit Standard Industrial Classification (SIC) code and exclude stocks from the Agriculture, Forestry, and Fishing (SIC codes: 01 to 09) and Public Administration (SIC codes: 91 to 99) classifications.

Employment data by industry are from the U.S. Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW), which covers about 97% of all wage and salary civilian employment in the United States.⁴ I consider two industry aggregation levels: the 3-digit SIC code referring to an industry group and the 2-digit SIC code referring to a major industry group. For each industry i in month t , I calculate its employment growth over the past $H = 1$ to 5 years: $\Delta \text{Industry Employment}_{i,t,H}$. Because employment growth is measured over an entire year (e.g., relating the employment level of March to the employment level of March the year before), seasonality effects are accounted for.

⁴See: <http://www.bls.gov/cew/cewfaq.htm>.

The QCEW employment data classified by the SIC codes are in place between 1975 and 2000, but after that the QCEW started using the North American Industry Classification System (NAICS). Because industry classification in CRSP is mainly based on SIC codes,⁵ I convert the employment figures based on NAICS to SIC using the conversion tables provided by the BLS.⁶ The methodology applied is the same as that used for the NBER-CES Manufacturing Industry Database, though I extend the scope beyond manufacturing industries (for further details, see [Becker, Gray and Marvakov, 2013](#)). The BLS reconstructed the NAICS-based data files for some years prior to 2001, which provides a check on how well the conversion from NAICS to SIC worked. The cross-sectional correlation in December 2000 between the original SIC-based and the NAICS-to-SIC-converted 5-year employment growth is quite high, with a correlation coefficient of 0.82 for the 2-digit SIC and 0.74 for the 3-digit SIC industries. For industry employment growth figures after December 2000, I first convert the NAICS industry employment levels to SIC industry levels, then calculate employment growth over one to five years, based on these converted employment levels. Some sudden shifts in the QCEW levels of employment are not the result of economic activities, but rather are due to reclassifications by the BLS.⁷ To mitigate the erroneous effect of these outlier observations, I omit observations of industry employment growth over the 99th percentile or below the 1st percentile of the sample distributions.

I merge the CRSP stock data with industry employment growth based on 3-digit and 2-digit SIC classifications, which reflect industry and major industry groups, respectively. The merge is done on the industry portfolio level (Section 4) and on the stock level (Section 5). The average number of major industry groups (2-digit SIC code) in the merged data set is 62; the number of industry groups (3-digit SIC code) is 182. The SIC system would also provide a 4-digit industry classification, but for most Nasdaq firms, 4-digit SIC

⁵In the CRSP Stock Databases, NAICS codes are only available since June, 2004.

⁶Conversion tables can be accessed at: <http://www.bls.gov/ces/cesnaics02.htm>.

⁷See: <http://www.bls.gov/cew/cewfaq.htm>.

codes are not available in the CRSP database. Moreover, a very fine industry classification might result in inaccuracies.⁸

The QCEW employment data are available starting in January 1975. Because employment growth is calculated over time spans of up to five years, the sample period considered in this study runs from January 1980 to December 2012. Table 1 provides summary statistics on industry employment growth (at the industry portfolio and firm level), industry portfolio factor loadings, and stock characteristics. A strong cross-sectional variation in employment occurs across industries. For example, the 95th percentile of 5-year employment growth is 38.36%, whereas the 5th percentile is -23.64% (Table 1, Panel A.2). That is, whereas in some industries employment expands substantially, in others, it contracts considerably. The estimated risk loadings for the market, size, and value factors also show a strong cross-sectional dispersion.

Figure 1 displays the cross-sectional distribution percentiles of employment growth across different industries (3-digit SIC classification) over time, measuring employment growth over the horizons of one year and five years. Looking at one-year employment growth in Figure 1(a), we observe the well-known pro-cyclical shifts of employment over the business cycle. The cross-sectional variation in the employment growth distribution also is quite large, in both economic expansions and recessions. This finding is consistent with previous studies (e.g. Davis and Haltiwanger, 1992) that document large job creation and destruction rates at the firm plant level. Measuring employment growth over five years, smooths out much of the business cycle variations as Figure 1(b) reveals. This finding confirms the suspicion by Fama and French (1996) that technology shocks and

⁸The original data source for SIC codes are the company's filings with the Securities and Exchange Commission (SEC) but there are no strict reviewing procedures regarding the firm's SIC code. If a firm changes its industry over time, it would not necessarily be reflected in the data. Such a measurement error is more likely for the application of a very fine industry classification (4-digit SIC code), whereas it is relatively unlikely that a firm would switch from an entire industry group (3-digit SIC code) or major industry group (2-digit SIC code) to another.

alike affect various industries very differently, without having necessarily much effect on the aggregate economy. The strong cross-sectional variation in employment growth across industries represents a considerable risk to the labor income of some investors, if their human capital is specialized and specific to an industry in distress. This risk emerges in addition to the labor income risk that originates from the business cycle.

4 Industries' exposure to the value factor and employment growth

In their work on industry cost of capital, [Fama and French \(1997\)](#) document that industries' risk loadings for the market, size, and value factors vary considerably over time. With respect to the value premium, industries' portfolio returns behave like growth stocks in some periods and like value stocks in others. I seek to determine what explains the cross-sectional differences in industries' risk loadings to the value premium.

According to the specialized human capital hypothesis, workers in distressed industries do not want to invest in these industries, because a negative shock to the industry would correlate with their human capital. Specialized human capital comes at risk if employment strongly contracts in the industry to which the firm belongs. The skills needed in that industry are in less demand, and the employee faces the risk of unemployment. Unemployment risk for the employee gets aggravated, because finding a new job that requires the same industry-specific human capital is harder if those industry-specific skills are less in demand; it even could become impossible if such jobs are obsolete. Thus, employees with human capital specialized for a certain industry should be less willing to hold stocks in that industry, which potentially results in a premium for distressed firms/industries (i.e. the value premium). Relating this reasoning to the time-varying value loadings of industry portfolios, I investigate the following question: Can industries

in which employment contracts (such that specialized human capital is at risk) also be characterized as industries with a high exposure to the value factor?

To answer this question, I proceed in two steps. First, I form value-weighted industry portfolios and estimate their risk loadings. Second, I regress the industries' value factor loading on the industries' employment growth in a cross-sectional regression. I form value-weighted industry portfolios based on different SIC aggregation levels (2-digit and 3-digit codes). To avoid idiosyncratic effects, each industry portfolio must have at least five stocks at each point in time. To estimate the value factor risk loading, I follow [Fama and French \(1997\)](#) and run a time-series regression of the three-factor model using a rolling window of 60 months:

$$R_{i,t} - R_t^f = a_i + \beta_i^m MKTRF_t + \beta_i^s SMB_t^{FF} + \beta_i^v VMG_t^{FF} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t} - R_t^f$ is the value-weighted return of industry i over the risk-free rate, MKTRF is the market excess return, and SMB^{FF} ("Small-Minus-Big") and VMG^{FF} ("Value-Minus-Growth") are the risk factors associated with the size and value anomaly, respectively ([Fama and French, 1993](#)).⁹ The VMG^{FF} factor is also known as the "High-Minus-Low" (HML) factor in reference to the book-to-market ratio (B/M) when it serves as a measure for value (high B/M) and growth (low B/M) firms. I use the more general VMG notation as also done by [Fama and French \(2006\)](#). In this value factor construction, VMG^{FF} is an equal-weighted portfolio of two value-weighted Value-Minus-Growth portfolios: that in small stocks and that in big stocks.¹⁰

⁹Risk factors come from Kenneth French's home page: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

¹⁰[Fama and French \(1993\)](#) construct their risk factors using a 2×3 double sort on the basis of size (cutoff: median) and book-to-market (cutoffs: 30th and 70th percentile), resulting in six value-weighted portfolios. The construction of the size and value factors is as follows: $SMB^{FF} = 1/3(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - 1/3(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$, and $VMG^{FF} = HML = 1/2(\text{Small Value} + \text{Big Value}) - 1/2(\text{Small Growth} + \text{Big Growth})$.

The rolling time-series regression from Equation (1) yields, for each point in time and for each industry, their risk exposure to the value factor $\hat{\beta}_i^v$, which I seek to explain in the next step. Here I run the following cross-sectional regression at each point in time:

$$\hat{\beta}_i^v = \gamma_0 + \gamma_1 \Delta \text{Industry Employment}_{i,H} + \eta_{i,h}, \quad (2)$$

where the dependent variable $\hat{\beta}_i^v$ is the estimated value factor risk loading of industry i , explained by employment growth in that industry ($\Delta \text{Industry Employment}_{i,H}$). Industry employment growth is measured over different horizons H , ranging from one to five years. $\hat{\beta}_i^v$ represents the estimate of the true β_i^v and is therefore measured with error. Because the measurement error occurs in the dependent variable, estimates for $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are unbiased, but not efficient. That is, the standard errors are larger than if we knew the true factor loadings. Thus, the measurement error reduces statistical power and makes it harder to reject the null hypothesis. With respect to the estimation method, I follow the asset pricing tradition and report time series averages of the cross-sectional coefficient estimates; t-statistics are based on time-series standard deviations (Fama and MacBeth, 1973), adjusted for serial correlation in the residuals, following Newey and West (1987).

For the results of the cross-sectional regression see Table 2. Panel A reports estimates for major industry groups, and Panel B reports estimates for industry groups. The coefficient of employment growth is negative and declines monotonically with a longer horizon for measuring employment growth. In Panel B, γ_1 is -0.05 (t-value: -1.52) if employment growth is measured over one year, and it decreases to -0.13 (t-value: -2.65) for a measurement period of five years. This finding is consistent with the specialized human capital hypothesis. Industries that face employment contraction for a longer time have, on average, greater exposure to the value factor. Industries in which employment expands instead have a low average exposure to the value factor. Because the estimates

are standardized, we can evaluate their economic significance too. If employment growth is measured over a five-year horizon, a one standard deviation increase in employment growth is associated with a decline of the estimated value factor loading equal to 0.13 (Panel B). The average coefficient of determination R^2 amounts to 4.51% in the five-year horizon regression. However, R^2 is difficult to interpret in this context, because it merely measures the share of explained variation of the *estimated* risk loadings, not that of *true* risk loadings. The factor loadings in this setting possess considerable estimation error (cf. [Fama and French, 1997](#)).

The preceding analysis indicates a negative relationship between employment growth and the loading on the value factor. A related question in this context is whether employment growth also is reflected in the size and market loading of each industry. To answer this question I re-run the cross-sectional regression for the size and value loading, using employment growth over five years (i.e., the specification, with the strongest results for the value loading) as an explanatory variable, whose results are shown in Table 3. For both the size and the market loading, the Fama-MacBeth cross-sectional regression yields an insignificant coefficient for employment growth, robust for both industry aggregations (2- and 3-digit SIC). Furthermore, I investigate whether the time-varying market beta of the CAPM relates to employment growth in the cross-section. In this case, the employment growth coefficient also is insignificant at conventional significance levels. Taken together, these results suggest that industry employment growth is distinctly related to the value risk factor.

The regression framework of Equation (2) imposes a linear relationship between the value factor loading and employment growth but this functional form may be incorrect. To study the relationship in more detail, I sort the industry portfolios in different groups on the basis of their past employment growth and report the average beta loading in each group. Such a sorting also alleviates the potentially strong influence of extreme

observations that can be present in a regression setting. Table 4 shows the results of this sorting exercise. Panel A reports the results for major industry groups (2-digit SIC codes), Panel B reports the results for industry groups (3-digit SIC codes). With only 62 major industry groups, Panel A identifies two groups with the median as a cutoff, whereas Panel B reflects groupings based on quintiles. I focus on the quintile sorts in the following interpretations.

As before, we observe that industries with low employment growth tend to have high value factor loadings, and industries with high employment growth tend to have low value factor loadings. Based on the one-year employment growth sort, the average value loading for the bottom 20% is 0.18, whereas the average loading for the top 20% amounts to 0.11, which represents a reduction by 41.9%. Although the average risk value loading is significantly different from zero at the 1% level for the low employment quintile, it is insignificant for the high employment growth quintile. The difference between the 5th and 1st quintile cannot be qualified as statistically significant for the one year measurement horizon though. Moving from left to right, the economic magnitude and statistical significance of the difference between high and low employment growth quintiles increase with the horizon over which I measure employment growth. Sorting industries on five-year employment growth, the average value loading for the bottom 20% is 0.23, and the average loading for the top 20% is close to zero (i.e. 0.02), which represents a reduction of 90.6%. The differential of 0.21 is statistically significant at the 1% level. Sortings based on the coarser 2-digit SIC codes (Panel A) show a similar picture. The difference in beta loadings between low and high employment growth increases with the horizon. The intuition behind this finding is as follows: If employment declines in an industry in one year, it represents a noisy measure of whether human capital is in distress in that industry. If employment instead declines in an industry over a five-year horizon, it constitutes a much clearer indication that the human capital of the industry is in distress.

The quintile sorts of Panel B reveal that the beta loading for value declines fairly linearly with employment growth when employment is measured over shorter horizons of one to two years, but some non-linearities arise for longer horizons. In particular, the beta loading decreases considerably when moving from the 4th quintile to the 5th quintile for the five-year employment growth measure.

Thus, the regression analysis and the sorting exercise concur in their findings: Industries in which employment contracts over a long period of time have a significantly higher exposure to the value factor than do industries in which employment expands. This finding is in line with [Fama and French's \(1996\)](#) conjecture that specialized human capital can explain the value premium. Distressed industries, in which employment contracts and specialized human capital is at risk, tend to behave like value firms, with a strong loading on the value factor. Employees do not want to hold these industries, which drives prices down, and in equilibrium, results in higher expected returns for these industries. The high exposure to the value factor of low employment growth industries implies higher expected returns for them, which is in line with the provided reasoning.

5 Industry employment growth and expected returns

5.1 Cross-sectional predictive regression

In this section, I directly investigate the relationship between industry employment growth and expected returns in the cross section. Instead of portfolios, the data set for this analysis consists of firm-month observations. I assign each stock an industry employment growth value based on its 3-digit SIC code. I chose the 3-digit SIC classification, because the 2-digit SIC classification is too coarse, representing only 62 industries on average in the cross section. To measure the distress of specialized human capital in an industry, I use employment growth measured over a horizon of five years. To mitigate the strong

effect of illiquid stocks in the cross-sectional regression, I exclude penny stocks, defined according to the convention in prior literature (see e.g. [Jegadeesh and Titman, 2001](#)), as stocks with a price below five dollars.

To relate employment growth to expected return, I run monthly cross-sectional regressions predicting the return in month t with firm characteristics in month $t - 1$. As before, I use the [Fama and MacBeth \(1973\)](#) procedure and compute [Newey and West \(1987\)](#) standard errors. Table 5 contains the predictive regression results. Column (1) shows the most simple specification, in which future returns are regressed on current industry employment growth. The average slope coefficient is negative with a value of -0.67 , statistically significant at the 1% level with a t -value of 3.96. This negative slope coefficient means that firms belonging to industries with contracting employment on average have higher expected returns than firms in industries where employment is expanding. To gauge the economic significance of this effect, I compare an industry where employment contracted by 17.01% (10th percentile) against an industry where employment expanded by 31.50% (90th percentile), which yields a monthly return differential of -32.5 basis points, translating into an annualized return differential of -3.83% .

The specification in Column (1) uses five-year employment growth at month $t - 1$ to predict returns in month t . This specification does not take into account the publication lag of employment data though, which usually is published with a delay of five to six months.¹¹ Whether this time lag is important, depends on the question asked. To explain the variation in expected returns in the cross section of stocks, the preceding specification may already be appropriate. Information about a negative shock on their human capital has reached many affected employees at that time (for example, the employees fired or those still employed at a firm that has fired a large fraction of its employees). People affected by the shock adjust their portfolio accordingly, generating the observed return

¹¹See: <http://www.bls.gov/cew/cewfaq.htm>.

premium. However, for outsiders seeking to form a trading strategy or a hedging portfolio, this information is not easily available, so they have to rely on the official BLS publication, which is only available with a time lag. Moreover, it is common practice to update predictive variables, such as market capitalization and book-to-market, only once a year. Therefore, I construct a second employment growth variable, which for June of year t uses employment growth measured in December of year $t - 1$ (i.e. a publication lag of 6 months). This employment growth measure is updated only once a year, every June, and is denoted by an asterisk, $\Delta Industry Employment^*$. Column (2) of Table 5 shows the results of the univariate predictive regression using the second industry employment growth variable, which resemble those from the first employment growth variable in Column (1).

The specifications in Columns (3) and (4) also include two predictive variables, *Size* (natural log of market capitalization in June of each year) and Jegadeesh and Titman's (1993) *Momentum* (cumulative return from month $t - 12$ to month $t - 2$), as control variables. Both employment growth variables remain significant, with a coefficient estimate of similar economic magnitude. The coefficient for the *Size* control variable is insignificant, in accordance with prior studies that document the disappearance of the size effect after the 1980s. The *Momentum* coefficient is positive and significant at the 10% level.¹²

In Columns (5) and (6), I compare my predictive regression results with the standard benchmark model containing *B/M* (log book-to-market ratio) and the *Size* and *Momentum* controls. *B/M* yields a significantly positive coefficient of 0.32, meaning that value stocks outperform growth stocks. Comparing the stocks in the 90th percentile with stocks in the 10th percentile of *B/M* yields an annualized return differential of 7.63%. In Columns (7) and (8), I investigate if *B/M* offers additional marginal explanatory power, beyond

¹²The relatively weak results for momentum arise because the sample period contains the momentum crash in 2009 (see e.g. Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014). The specification in Column (6) re-run for a sample period July 1981 - December 2008, yields a *Momentum* coefficient of 0.73 with a t-value of 4.68.

industry employment growth, by first orthogonalizing B/M with respect to industry employment growth and then including the orthogonalized book-to-market ratio (B/M^\perp) in the regression. The coefficient of B/M^\perp remains significant, suggesting that B/M contains information in addition to that reflected by industry employment growth. This finding is not surprising; industry employment growth can capture inter-industry distress, but it cannot account for intra-industry distress.

5.2 Pervasiveness across different size groups

A disadvantage of cross-sectional predictive regressions is the potentially large influence of small stocks. Extreme observations of small and micro stocks might dominate the effects, because market capitalization is very concentrated in the stock market, leading to a very large number of small stocks (Fama and French, 2008). It is therefore important to establish that the effect of a predictive variable is pervasive across different market capitalization groups. To check whether the effect of a predictive variable is pervasive, Fama and French (2008) suggest running predictive regressions separately for different market capitalization groups. To group the stocks by size, I follow their approach and use the NYSE market capitalization percentiles as breakpoints. Small and big stocks are separated at the median; micro caps are defined as stocks below the 20th percentile.

Table 6 shows the cross-sectional regression results for different market capitalization groups: small, big, and micro stocks as well as a sample that excludes micro stocks. Panel A shows the predictive regression results for industry employment growth, controlling for size and momentum. The effect of industry employment growth on expected returns is pervasive across different market capitalization groups. For all sub-samples, the coefficients associated with industry employment growth remain statistically significant at the 5% level and are sizable, economically speaking. The effect of industry employment growth on expected returns is to some degree weaker among big stocks, with a coefficient estimate

of -0.44 , but it remains statistically significant at the 5% level. The predictive power of industry employment growth also is not driven by micro stocks. That is, even after excluding micro stocks, the coefficient remains sizable (-0.56) and significant at the 1% level.

Panel B shows the predictive regression results for the book-to-market ratio (controlling for size and momentum) in comparison. As documented in previous studies (Kothari, Shanken and Sloan, 1995; Loughran, 1997; Fama and French, 2008), I find that the value premium is considerably lower for big than for small stocks. Comparing the overall sample to that of big stocks, the coefficient for the book-to-market ratio decreases by more than half, from 0.31 (Table 5) to 0.14. Thus, much of the predictive power of the book-to-market ratio can be attributed to its very strong effect among micro stocks. Panel C depicts the joint model of industry employment growth and the book-to-market; B/M shows the weakest marginal explanatory power for big stocks but remains statistically significant at the 10% level.

Overall, the predictive power of industry employment growth is pervasive across all size groups. Moving from the 90th to the 10th percentile of the sample distribution leads to an annual return differential ranging between -2.53% and -4.11% .

5.3 Hedging portfolio returns

The cross-sectional predictive regressions document a negative relationship between industry employment growth and expected returns. In this section, I consider value-weighted hedging portfolio returns. Following common practice, I divide stocks into three portfolios (low, mid, and high), according to the past employment growth of their industry and form value-weighted portfolios. The breakpoints are the 30th and 70th percentiles to allow for comparison with the Fama-French factors. Again, I lag employment growth by six months and update the portfolio allocation once a year, in June. That is, portfolio allocation

for July to June of the next year is based on the five-year industry employment growth, measured at the end of December of the previous year.

Table 7 shows the average returns of the three value-weighted portfolios formed on basis of industry employment growth and the portfolios' pricing errors for the CAPM and Fama-French three-factor model. Consistent with the findings of the cross-sectional regression, the average excess returns are higher for low employment growth industries than for high employment growth industries. The return difference between the low and high industry employment growth portfolios is -20.25 basis points (bp), though the difference cannot be qualified as statistically significant at conventional levels.

The real puzzle arises, if this returns spread should be explained by the CAPM. For the CAPM, assets with high expected returns should be associated with a high market beta. However, the observed pattern of market betas is just the opposite: The low and mid industry employment growth portfolios possess low market betas (0.94 and 0.95 , respectively), which are statistically significantly less than one. The market beta for the high industry employment growth portfolio instead is statistically significantly greater than one at a value of 1.12 . The CAPM yields a positive pricing error of 18.79 bp (t-value: 2.02) for the low employment growth portfolio and a negative pricing error of -11.55 bp (t-value: -1.38) for the high employment growth portfolio. The return difference between the low and high portfolios amounts to -30.34 bp (t-value: -2.10), which translates into an annualized return of -3.58% . Thus, the CAPM fails to price the industry employment growth portfolios, because the market beta loadings relate negatively to expected average returns. Just the same is observed if the CAPM is used to price value and growth portfolios in the period after 1963 (e.g., [Fama and French, 2006](#)). Value stocks with higher expected returns have lower market betas than growth stocks. In this regard, the value premium and industry employment growth premium resemble each other.

In contrast with the CAPM, the Fama-French three-factor model can account for the spread in portfolios sorted by industry employment growth, as shown in the last panel of Table 7. All pricing errors are insignificant, and of small economic magnitude, ranging between 4.27 and 5.90 bp. The spread between the low and high employment growth portfolios amounts to 10.13 bp statistically non-different from zero. The ability of the Fama-French model to price the employment growth portfolios stems from the loadings on the value factor (VMG^{FF}). The low industry employment growth portfolio has a significant positive loading (0.27, t-value: 6.13), whereas the high industry employment growth portfolio has a significant negative loading (-0.15, t-value: -3.52).

The return difference between portfolios of low and high employment growth can be interpreted as the return of a hedging portfolio for unemployment risk in distressed industries. Employees in distressed industries, in which employment is strongly contracting, move their capital away (disinvest), because they dislike holding stocks for which the negative shock to the industry correlates with their specialized human capital in that industry. Holding stocks in these distressed industries commands a risk premium; investors prefer instead to hold stocks that are not distressed, which results in lower expected returns for the latter stocks. Thus, a hedge portfolio for specialized human capital invests in industries with employment growth but shorts industries with unemployment growth. I denote this hedging portfolio “Employment-Minus-Unemployment” or EMU. In the following, I will investigate the properties of the market-beta-hedged EMU portfolio EMU^\perp , which is orthogonal with respect to the market excess return (MKTRF).

Table 8 compares the performance of different EMU^\perp factors to the parallel Value-Minus-Growth factor, adjusted for market beta risk or VMG^\perp . I investigate the different factors for the entire set of stocks and based on small and big stocks, split along the NYSE median market capitalization. The value/growth portfolios are from Kenneth French’s home page and are constructed by sorting stocks along their book-to-market value, with

cutoffs at the 30th and 70th percentiles. The VMG portfolio is long in the value-weighted portfolio of high book-to-market stocks and short in the value-weighted portfolio of low book-to-market stocks. The VMG^\perp factor is the value-minus-growth factor orthogonalized with respect to the market factor MKTRF.

As Table 7 previously revealed, the EMU^\perp factor is priced with a monthly return of 30.34 bp, significant at the 5% level. Table 8 additionally shows that the effect is pervasive and of similar economic magnitude across both small and big stocks. The monthly return of EMU^\perp for big stocks is 37.59 bp, and for small stocks, it is 27.49 bp, significant at the 5% and 10% levels, respectively, which translates into annualized returns of -4.42% and -3.25% . Thus, the premium related to employment growth in industries is priced in the stock market and pervasive across small and big stocks.

The second part of Panel A shows the value premium in comparison. The overall premium for VMG^\perp using all stocks amounts to 25.24 bp (annualized return of 3.07%) but is insignificant at the 10% significance level. When comparing the premium across small and big stocks, we find that most of the value premium is generated in small stocks, where the monthly return is 81.40 bp (annualized return of 10.22%), which is also highly statistically significant. The value premium in small stocks is more than five times greater than that of big stocks, with 15.15 bp (annualized return of 1.83%), which is not statistically significantly different from zero at any conventional significance level. The value weighting of returns additionally reduces the influence of smaller stocks, resulting in an insignificant value premium for big stocks. Thus, much of the value premium's strong performance can be attributed to its strong performance among small stocks.

How do EMU^\perp and VMG^\perp relate? Using time-series regressions, I investigate whether one factor can price the other. Because EMU^\perp and VMG^\perp are both zero-investment portfolios, the intercept of a time-series regression of one factor regressed on the other represents the pricing error. First, I investigate whether VMG^\perp can price EMU^\perp . The

pricing error is the smallest for small stocks with a value of 7.76 bp and not statistically different from zero. The pricing errors are insignificant at the 10% level when all stocks or big stocks are considered, though only marginally (t-value: -1.60). Economically speaking, the pricing errors are quite large when compared with the original factor premium to be explained – particularly for big stocks, where the EMU^\perp return is -27.49 bp and the pricing error is 22.04 bp.¹³ Second, I investigate whether EMU^\perp can price VMG^\perp . Across all stocks, EMU^\perp can sufficiently explain the value premium with an insignificant pricing error of 13.35 bp. The pricing error is particularly small for big stocks, though in this case the premium here was not very large to begin. For small stocks, the pricing error decreases by around 28% but is still economically large at 58.79 bp and statistically significant. Even though EMU^\perp can explain the value premium in the entire stock market, it cannot account for the strong value premium among small stocks, also known as the small-growth puzzle. The strong value premium among small stocks is largely due to the very low returns of small growth firms, but not because small value firms have very high returns (Fama and French, 2006).

Figure 2 illustrates the relationship between EMU^\perp and VMG^\perp by plotting their rolling 12-month returns over time, providing an intuition for the generated return premia. Looking solely at the value factor, no clear business cycle pattern emerges (see also Lakonishok et al., 1994). In some recessions, VMG^\perp has negative returns, whereas in others, it reveals positive returns. For the extended sample from 1963 to 2012, the return differential between value and growth firms overall is 4.03%, and it is virtually the same in expansions (4.02%) or recessions (4.09%). This finding is puzzling from a rational asset pricing perspective: An asset that has poor payoffs in bad times, when the marginal utility

¹³The pricing error for the time-series regression of EMU^\perp on VMG^\perp of 21.73 bp is larger than that reported by the Fama-French model in Table 7, Panel C (10.13 bp). This difference is caused by the distinct methods used to construct the VMG factors. The value factor constructed by Fama and French (1993) VMG^{FF} is an equal-weighted portfolio of VMG in small stocks and VMG in large stocks, resulting in a higher value premium. See also footnote 10.

of wealth is high, must offer higher expected returns; an asset that has high payoffs in bad times instead has lower expected returns in equilibrium. Because the value strategy offers a positive average return, it seemingly should have poor returns in bad times, that is during recessions. However, the results do not support this prediction. Particularly surprising are the negative returns during the booming years of the late 1990s, followed by strong positive returns during the recession of 2001.

So why are investors reluctant to follow a value investment strategy, if it is unrelated to bad times indicated by obvious business cycle variables? The answer may lie in how we define “bad times”. Even though the late 1990s were overall boom times, during the information technological revolution, many skills and jobs became obsolete, representing a negative shock to the specialized human capital of a large fraction of the population. The people affected by this negative shock are less willing to hold the shares of companies that are correlated with the same shock, and prefer stocks which are less correlated to the shock. The EMU^\perp portfolio mimics this behavior, shorting industries where employment contracts and investing in industries where employment expands. The returns of EMU^\perp are strongly positive during the late 1990s period, in contrast to VMG^\perp , which has negative returns during that time. The general pattern that emerges is a negative relationship between EMU^\perp and VMG^\perp . Because EMU^\perp acts as a hedging portfolio against negative shocks to specialized human capital it has a negative premium of -3.58% , whereas VMG^\perp , with its inverse payoff structure, has a positive premium of 3.07% .

6 Concluding remarks

A household dislikes assets whose payoffs correlate with negative shock to its specialized human capital, commanding a risk premium for holding these. The results documented herein are consistent with this specialized human capital hypothesis for the value premium.

Measuring shocks to industry-specific human capital by employment growth in that industry, I find that industries marked by employment contraction possess a significantly higher exposure to the value factor than do industries where employment expands. Using cross-sectional predictive regressions and hedging portfolios, I document that stocks belonging to industries with low employment growth have higher expected returns than firms belonging to industries with high employment growth. This return premium, related to specialized human capital, is pervasive across different groups of market capitalization.

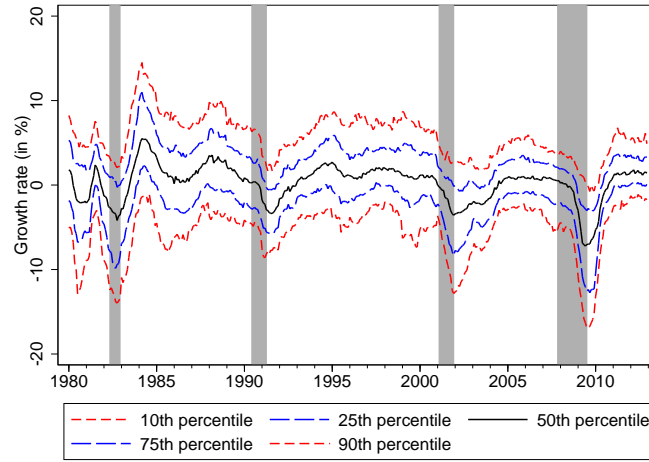
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(a) One-year industry employment growth



(b) Five-year industry employment growth

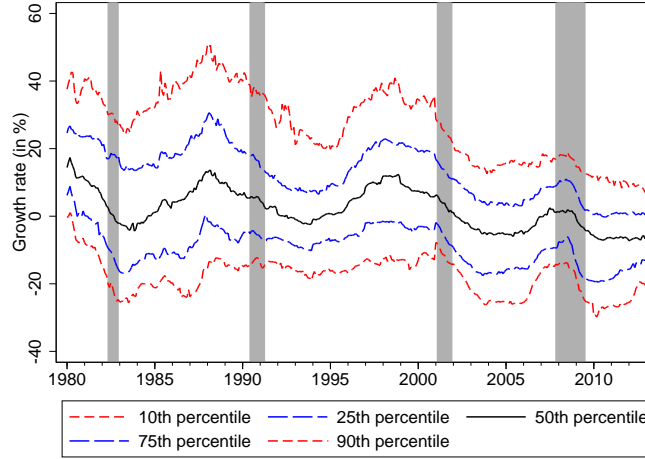


Figure 1:
Distribution percentiles of industry employment growth over time

This figure displays cross-sectional distribution percentiles (10th to 90th) of industry employment growth (in %) over time. Employment growth is measured over horizons of one year in Figure 1(a) and five years in Figure 1(b). Industries are classified on the basis of 3-digit SIC codes, with an average number of 182 industries. The sample period is January 1980 to December 2012; shaded areas indicate recession periods, as defined by the National Bureau of Economic Research (NBER).

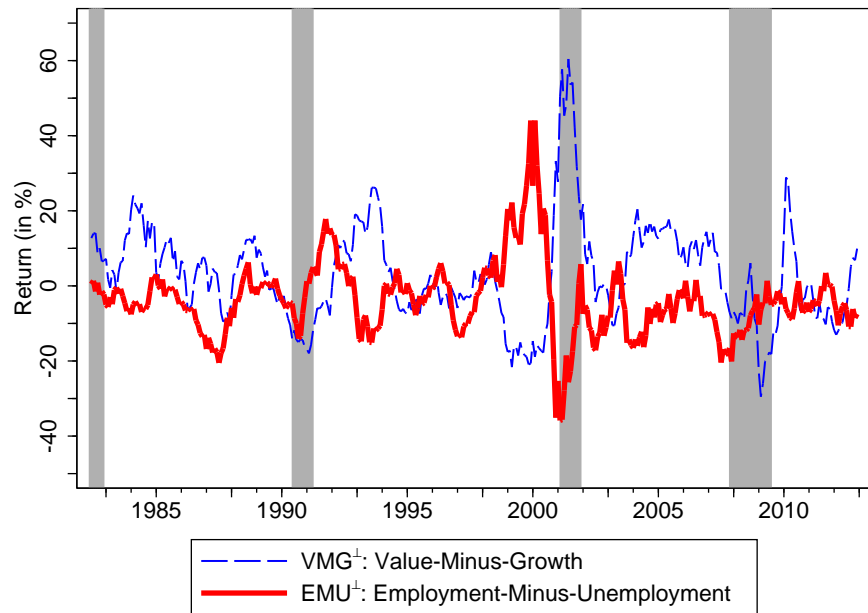


Figure 2:
Performance of different investment strategies over time

This figure displays the rolling 12-month returns (in %) of a value investment strategy (VMG^{\perp}) and a strategy to hedge unemployment risk in distressed industries (EMU^{\perp}). For the VMG^{\perp} (EMU^{\perp}) factor, stocks are sorted on the basis of their book-to-market value (the employment growth of the industry to which the firm belongs), and value-weighted portfolios are formed above and below the 30th and 70th percentiles. The VMG^{\perp} portfolio is long in the value portfolio and short in the growth portfolio and orthogonalized with respect to the market excess return. The EMU^{\perp} portfolio is long in industries where employment expands and short in industries where employment contracts, in relative terms; it also is orthogonalized with respect to the market excess return. The sample period is July 1981 to December 2012; shaded areas indicate recession periods, as defined by the National Bureau of Economic Research (NBER).

Table 1:
Summary statistics

This table contains summary statistics for industry-level data (Panel A.1 and A.2) and firm-level data (Panel B). For each variable, it provides time-series averages of the cross-sectional mean, standard deviation (SD), and the 5th to 95th percentiles. The industry-level variables (Panel A.1 and A.2) are industry employment growth (in %) over the horizons of one to five years, and the risk factor exposure loadings to the market ($\hat{\beta}_i^m$), size ($\hat{\beta}_i^s$), and value ($\hat{\beta}_i^v$) factors using the Fama-French three-factor model with a rolling estimation window of 60 months. Statistics in Panel A.1 are based on the 2-digit SIC code classification, with an average number of 62 industries, statistics in Panel A.2 are based on the 3-digit SIC code classification, with an average number of 182 industries. Panel B shows summary statistics for the firm-level data, matching 3-digit SIC code employment growth data to each firm. It shows summary statistics for the five-year industry employment growth, log market capitalization (*Size*), log book-to-market ratio (*B/M*) and the cumulative return (in %) from month $t - 12$ to month $t - 2$ (*Momentum*). The sample period is January 1980 to December 2012.

Variable:	Mean	SD	Percentiles:						
			5th	10th	25th	50th	75th	90th	95th
Panel A.1: Industry-level data: Major industry groups (2-digit SIC code)									
$\Delta Ind. Employment$:									
1 year	0.48	3.91	-6.12	-4.28	-1.67	0.68	2.72	4.67	6.22
2 years	1.18	7.15	-10.57	-7.51	-2.86	1.48	5.19	8.86	12.34
3 years	2.04	10.14	-14.66	-10.16	-3.87	2.34	7.61	13.48	18.21
4 years	3.14	13.00	-18.39	-12.62	-4.81	3.37	10.26	18.34	24.91
5 years	4.57	15.61	-20.94	-14.38	-5.24	4.83	13.25	22.81	31.33
$\hat{\beta}^m$	1.07	0.27	0.66	0.75	0.88	1.05	1.22	1.41	1.55
$\hat{\beta}^s$	0.35	0.43	-0.35	-0.21	0.06	0.35	0.65	0.92	1.08
$\hat{\beta}^v$	0.15	0.46	-0.65	-0.44	-0.13	0.18	0.46	0.72	0.86
Panel A.2: Industry-level data: Industry groups (3-digit SIC code)									
$\Delta Ind. Employment$:									
1 year	0.18	4.88	-7.63	-5.56	-2.63	0.25	2.95	5.76	7.97
2 years	0.60	8.60	-12.82	-9.44	-4.65	0.48	5.37	10.72	15.12
3 years	1.22	12.04	-16.89	-12.77	-6.37	0.83	7.69	15.91	22.19
4 years	2.09	15.37	-20.54	-15.55	-7.93	1.41	10.25	21.52	29.68
5 years	3.34	18.67	-23.64	-17.68	-9.06	2.14	13.07	27.17	38.36
$\hat{\beta}^m$	1.07	0.31	0.60	0.70	0.86	1.06	1.25	1.45	1.59
$\hat{\beta}^s$	0.41	0.49	-0.37	-0.22	0.08	0.40	0.73	1.04	1.25
$\hat{\beta}^v$	0.15	0.52	-0.76	-0.53	-0.15	0.17	0.48	0.77	0.96
Panel B: Firm-level data									
$\Delta Ind. Employment$ (5y):	4.90	18.85	-22.64	-17.01	-6.93	3.02	14.21	31.50	41.03
Size	5.64	1.77	3.01	3.46	4.34	5.48	6.78	8.05	8.81
B/M	-0.57	0.82	-2.01	-1.61	-1.02	-0.47	-0.04	0.31	0.55
Momentum	17.26	55.06	-42.39	-30.73	-11.23	9.41	33.50	67.35	99.96

Table 2:**Exposure to the value factor and industry employment growth:****Cross-sectional regressions**

This table shows the cross-sectional relationship between industries' value factor loading and industries' employment growth. Panel A reports the results based on major industry groups (2-digit SIC code) and Panel B reports the results based on industry groups (3-digit SIC code). I estimate, for each industry i , its exposure to the value factor $\hat{\beta}_i^v$ based on the Fama-French three-factor model using a rolling window of 60 months. Then I regress the $\hat{\beta}_i^v$ loading on the industries' employment growth in a cross-sectional [Fama and MacBeth \(1973\)](#) regression:

$$\hat{\beta}_i^v = \gamma_0 + \gamma_1 \Delta Ind. Employment_{i,H} + \eta_{i,H},$$

where $\Delta Industry Employment_{i,H}$ is the employment growth in industry i over the horizon H , ranging from 1 to 5 years. The table shows average coefficients and displays t-statistics based on Newey-West standard errors in parentheses. The sample period is January 1980 to December 2012.

	Horizon H (in years)				
	1	2	3	4	5
Panel A: Major industry groups (2-digit SIC code)					
<i>$\Delta Industry Employment$</i>	-0.05 (-1.52)	-0.05 (-1.36)	-0.08 (-1.92)	-0.10 (-2.29)	-0.12 (-2.66)
<i>Constant</i>	-0.01 (-1.79)	-0.01 (-2.54)	-0.01 (-2.90)	-0.01 (-2.71)	-0.01 (-2.25)
<i>R^2 (in %)</i>	3.47	3.14	3.32	3.60	4.28
Panel B: Industry groups (3-digit SIC code)					
<i>$\Delta Industry Employment$</i>	-0.05 (-1.55)	-0.08 (-1.91)	-0.10 (-2.15)	-0.12 (-2.38)	-0.13 (-2.65)
<i>Constant</i>	-0.00 (-0.46)	-0.00 (-0.48)	-0.00 (-0.80)	-0.00 (-0.53)	-0.00 (-0.34)
<i>R^2 (in %)</i>	2.87	3.35	3.83	4.23	4.51

Table 3:**Exposure to the market and size factor and industry employment growth**

This table repeats the [Fama and MacBeth \(1973\)](#) cross-sectional regression of Table 2 with industry portfolios' market, size, and value loading as dependent variable. I estimate, for each industry i , its exposure to the market ($\hat{\beta}_i^m$), size ($\hat{\beta}_i^s$), and value ($\hat{\beta}_i^v$) factors using the Fama-French three-factor model. I also estimate the market beta loading ($\hat{\beta}_i^m$) using the CAPM. As in Table 2, all loadings are estimated using a rolling window of 60 months. Then in a second step, I regress the beta loadings on the industries' five-year employment growth, using the Fama-MacBeth procedure. Panel A reports the results based on major industry groups (2-digit SIC codes), and Panel B reports those based on industry groups (3-digit SIC codes). The table shows average coefficients and displays t-statistics based on Newey-West standard errors in parentheses. The sample period is January 1980 to December 2012.

	Fama-French Model			CAPM
	$\hat{\beta}^m$	$\hat{\beta}^s$	$\hat{\beta}^v$	$\hat{\beta}^m$
Panel A: Major industry groups (2-digit SIC code)				
<i>ΔIndustry Employment</i>	0.07 (1.10)	0.04 (0.74)	-0.12 (-2.66)	0.12 (1.31)
<i>Constant</i>	-0.01 (-1.00)	-0.00 (-1.13)	-0.01 (-2.25)	-0.00 (-0.36)
<i>R² (in %)</i>	3.67	4.76	4.28	8.71
Panel B: Industry groups (3-digit SIC code)				
<i>ΔIndustry Employment</i>	0.04 (0.85)	0.03 (0.64)	-0.13 (-2.65)	0.07 (1.12)
<i>Constant</i>	0.01 (1.49)	-0.00 (-0.36)	-0.00 (-0.34)	0.00 (1.00)
<i>R² (in %)</i>	1.99	2.96	4.51	3.88

Table 4:**Exposure to the value factor and industry employment growth: Portfolio sorts**

This table shows industries' average factor loading $\hat{\beta}^v$ on the value factor, conditional on employment growth ($\Delta \text{Industry Employment}$). Panel A reports the results based on major industry groups (2-digit SIC code), whereas Panel B is based on industry groups (3-digit SIC code). For each industry, exposure to the value factor β^v is estimated using the Fama-French three-factor model with a rolling window of 60 months. For each month, industries are sorted into two or five groups, according to their employment growth (Panel A uses the median as a cutoff; Panel B uses quintiles), and the cross-sectional average is recorded. For each group, the table reports the time-series average of the cross-sectional average factor loading on the left-hand side and its t-value on the right-hand side. Industry employment growth is measured over horizons of one to five years. The sample period is January 1980 to December 2012.

$\Delta \text{Industry Employment}$	$\hat{\beta}^v$					t-value				
	Horizon H (in years)					Horizon H (in years)				
	1	2	3	4	5	1	2	3	4	5
Panel A: Major industry groups (2-digit SIC code)										
Low (1)	0.18	0.17	0.18	0.19	0.20	2.76	2.74	2.81	2.98	3.06
High (2)	0.13	0.13	0.12	0.10	0.10	1.55	1.55	1.45	1.34	1.25
Difference (1) - (2)	0.05	0.05	0.06	0.09	0.10	1.50	1.44	2.09	3.16	4.01
Panel B: Industry groups (3-digit SIC code)										
Low (1)	0.18	0.21	0.21	0.22	0.23	2.98	3.35	3.13	3.27	3.43
(2)	0.17	0.17	0.18	0.18	0.18	2.14	2.22	2.43	2.37	2.23
(3)	0.16	0.14	0.16	0.18	0.19	1.92	1.76	1.97	2.17	2.56
(4)	0.12	0.13	0.13	0.13	0.12	1.51	1.58	1.56	1.46	1.28
High (5)	0.11	0.08	0.05	0.03	0.02	1.15	0.88	0.54	0.35	0.23
Difference (1) - (5)	0.08	0.12	0.16	0.19	0.21	1.35	1.95	2.21	2.47	2.65

Table 5:**Industry employment growth and expected returns**

The table shows the average coefficients from monthly cross-sectional regressions to predict stock returns at month t with characteristics at time $t - 1$ using the [Fama and MacBeth \(1973\)](#) procedure. Here, $\Delta \text{Industry Employment (5y)}$ is the five-year industry employment growth and $\Delta \text{Industry Employment (5y)}^*$ is the five-year industry employment growth updated once a year in June using employment growth data from December the previous year (six-month publication lag). Size is the log of the market capitalization. B/M is the log of the book-to-market ratio. Size and B/M are updated once a year in June using the timing conventions, as in [Fama and French \(1992\)](#). B/M^\perp is the book-to-market ratio orthogonalized with respect to $\Delta \text{Industry Employment (5y)}^*$. Momentum is the cumulative return from month $t - 12$ to month $t - 2$. The t-statistics based on Newey-West standard errors are reported in the parenthesis. The sample period is July 1981 to December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \text{Ind. Employment (5y)}$	-0.67 (-3.96)		-0.58 (-4.29)					
$\Delta \text{Ind. Employment (5y)}^*$		-0.74 (-3.72)		-0.67 (-3.86)			-0.74 (-3.72)	-0.70 (-3.92)
B/M					0.32 (3.58)	0.31 (3.78)		
B/M^\perp							0.30 (3.60)	0.29 (3.76)
Size			-0.00 (-0.11)	-0.00 (-0.12)		0.02 (0.69)		0.02 (0.72)
Momentum			0.49 (1.76)	0.47 (1.71)		0.46 (1.69)		0.45 (1.68)
Constant	1.10 (6.35)	1.12 (6.28)	0.94 (2.54)	0.96 (2.62)	1.24 (6.32)	0.92 (2.61)	1.24 (6.19)	0.92 (2.63)
R^2 (in %)	0.50	0.52	2.33	2.33	1.13	2.87	1.43	3.14

Table 6:
Industry employment growth and expected returns:
Pervasiveness across different size groups

This table shows coefficient estimates of the return predictive regression using the Fama-MacBeth procedure for different groups of market capitalization. Small stocks are stocks below the median NYSE market capitalization and big stocks are those above it. Micro stocks are below the 20th percentile of the NYSE market capitalization. Here, $\Delta \text{Industry Employment (5y)}^*$ is the five-year industry employment growth, updated once a year in June using employment growth data from December the previous year (six-month publication lag). Size is the log of the market capitalization. B/M is the log of the book-to-market ratio. B/M^\perp is the book-to-market ratio orthogonalized with respect to $\Delta \text{Industry Employment (5y)}^*$. Momentum is the cumulative return from month $t - 12$ to month $t - 2$. For details, see Table 5. The t-statistics based on Newey-West standard errors are reported in the parenthesis. The sample period is July 1981 to December 2012.

	Small stocks	Big stocks	Micro stocks	Excluding micro stocks
Panel A: Industry employment growth				
$\Delta \text{Ind. Employment (5y)}^*$	-0.72 (-3.98)	-0.44 (-2.11)	-0.72 (-3.65)	-0.56 (-2.99)
Size	0.01 (0.22)	-0.06 (-1.20)	-0.03 (-0.50)	-0.03 (-0.77)
Momentum	0.51 (1.91)	0.37 (1.17)	0.55 (2.38)	0.42 (1.25)
Constant	0.87 (1.91)	1.41 (3.87)	1.00 (2.26)	1.16 (3.91)
R^2 (in %)	2.18	4.70	2.12	3.56
Panel B: Book-to-market				
B/M	0.35 (4.33)	0.14 (1.96)	0.38 (5.11)	0.21 (2.43)
Size	0.07 (1.43)	-0.04 (-0.89)	0.06 (1.11)	-0.02 (-0.49)
Momentum	0.49 (1.90)	0.36 (1.12)	0.54 (2.41)	0.42 (1.22)
Constant	0.73 (1.66)	1.33 (3.81)	0.78 (1.79)	1.16 (4.07)
R^2 (in %)	2.69	5.39	2.54	4.22
Panel C: Industry employment growth and book-to-market				
$\Delta \text{Ind. Employment (5y)}^*$	-0.76 (-4.21)	-0.45 (-2.13)	-0.76 (-3.83)	-0.57 (-2.99)
B/M^\perp	0.34 (4.38)	0.12 (1.80)	0.36 (5.27)	0.19 (2.28)
Size	0.07 (1.56)	-0.05 (-1.01)	0.06 (1.24)	-0.02 (-0.55)
Momentum	0.48 (1.89)	0.37 (1.17)	0.53 (2.39)	0.41 (1.20)
Constant	0.72 (1.68)	1.38 (3.83)	0.77 (1.79)	1.18 (4.03)
R^2 (in %)	2.93	6.14	2.79	4.69

Table 7:**Portfolio returns for industry employment growth**

The table shows the performance of value-weighted portfolios sorted on industry employment growth, with the 30th and 70th percentile as cutoffs and the difference between the high (3) and low (1) portfolio: (3) – (1). Panel A displays the mean excess return (in basis points). Panel B shows the market factor beta ($MKTRF$) and the pricing error α (in bp) for the CAPM. Panel C shows the beta for the market ($MKTRF$), size (SMB^{FF}), and value (VMG^{FF}) factors and the pricing error α (in bp) for the Fama-French three-factor model. The t-statistics are based on heteroscedasticity-consistent standard errors and provided in parentheses. For all coefficients except for the market beta, the null hypothesis is that the coefficient/mean is zero. For the market beta ($MKTRF$), the null hypothesis is that the beta equals one. The sample period is July 1981 to December 2012.

$\Delta Industry\ Employment^*$				
	Low (1)	(2)	High (3)	(3) – (1)
Panel A: Excess returns				
Mean	71.86 (3.03)	58.84 (2.58)	51.61 (1.89)	-20.25 (-1.34)
Panel B: CAPM				
MKTRF	0.93 (-2.74)	0.95 (-3.71)	1.11 (4.91)	
α	18.79 (2.02)	4.88 (0.95)	-11.55 (-1.38)	-30.34 (-2.10)
Panel C: Fama-French model:				
MKTRF	1.01 (0.28)	0.95 (-3.65)	1.07 (3.61)	
SMB^{FF}	-0.09 (-2.16)	-0.03 (-0.99)	0.01 (0.16)	
VMG^{FF}	0.27 (6.13)	-0.02 (-0.74)	-0.15 (-3.52)	
α	5.86 (0.72)	5.90 (1.11)	-4.27 (-0.50)	-10.13 (-0.74)

Table 8:**Value factor and distressed industry hedging portfolio**

This table shows the performance of the orthogonalized Value-Minus-Growth (VMG^\perp) and Employment-Minus-Unemployment factor (EMU^\perp) factors, as well as their relationship to each other. The table provides figures for the entire sample of stocks, as well as separately for small and big stocks. For the VMG^\perp (EMU^\perp) factor, stocks are sorted on the basis of their book-to-market value (the employment growth of the industry to which the firm belongs), and value-weighted portfolios are formed above and below the 30th and 70th percentiles. The VMG^\perp portfolio is long in the value portfolio and short in the growth portfolio and orthogonalized with respect to the market excess return. The EMU^\perp portfolio is long in industries where employment expands and short in industries where employment contracts, in relative terms; it also is orthogonalized with respect to the market excess return. Panel A displays average returns of VMG^\perp and EMU^\perp , along with their t-statistics. Panel B shows the slope coefficient β and intercept/pricing error α of a time-series regression with VMG^\perp as the dependent and EMU^\perp as an explanatory variable, and vice versa. The t-statistics are computed using heteroscedasticity-consistent standard errors. The sample period is July 1981 to December 2012.

	All stocks	Small stocks	Big stocks
Panel A: Average returns			
EMU^\perp			
Mean	-30.34 (-2.10)	-37.59 (-2.38)	-27.49 (-1.86)
VMG^\perp			
Mean	25.24 (1.65)	81.40 (4.96)	15.15 (0.94)
Panel B: Time-series regressions			
$EMU_t^\perp = \alpha + \beta VMG_t^\perp + \varepsilon_t$			
β	-0.36 (-6.01)	-0.56 (-8.64)	-0.36 (-5.82)
α	-21.26 (-1.54)	7.76 (0.54)	-22.04 (-1.60)
R^2 (in %)	14.35	33.51	15.28
$VMG_t^\perp = \alpha + \beta EMU_t^\perp + \varepsilon_t$			
β	-0.40 (-8.30)	-0.60 (-10.11)	-0.43 (-7.93)
α	13.14 (0.92)	58.79 (4.35)	3.47 (0.23)
R^2 (in %)	14.35	33.51	15.28